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A Trivariate Probit Analysis

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The Choice of the Working Sector in Italy: a Trivariate Probit Analysis

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Abstract

Using the Budget of Italian Families Survey by Banca d'Italia we analyse the sectoral choice of the Italian workers among the private, public and self-employed options. The choice is modelled using a trivariate probit which allows one to release the IIA hypothesis, imposed by the multinomial logit model. The validity of the IIA assumption is strongly rejected and a negative correlation between the utilities of working in the private and public sectors is found. Moreover, the significance of many individual specific variables in the estimated model supports the intuition of the existence some diversity among workers choosing the different sectors.

Keywords: multinomial probit model, IIA hypothesis testing, workers' sectoral choice, Italian labour market.

JEL classification: C31, C35, C52, J24.

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1 Introduction

The aim of the present study is to analyse the allocation of workers across the private, the public and the self-employed sectors. The distinction between these three sectors, we believe, reflects diversities in the preferences of individuals (and thus in "types" of individuals) entering them, even in the presence of rationing situations.

The empirical studies carried out up to now on the working "sectors", however, have mainly focused on the distinction among productive sectors (agriculture, manufacturing, services, etc.) and have only seldom adopted as a definition of "sector" the legal nature of the employer organizing the productive activity (be this public, private or self-employment). When this has happened, it has generally been in situations requiring the correction of a main equation from selection bias, like, for example, when estimating the wage differentials between the private and the public sectors[1] (in this case the analysis of the choice between the private and the public sector is needed precisely for the estimation of the selectivity bias in order to correct the wage equations) or in studies limited to only one sector, like, for example, in the analysis about self-employment.[2] This is why a systematic analysis of the "choice" of the sector as defined above is of great interest.

Another novel feature of the present study lies in the econometric approach chosen. We propose the adoption of a multinomial probit model, which has the advantage of taking into account the possible presence of correlation among the utilities deriving from each alternative. The estimation of a multinomial probit is not common in the literature, given the computational burden it requires. What is commonly estimated instead is a multinomial logit (imposing the absence of correlation between the utilities), whose estimation is much simpler and an option in all the microeconometric packages.[3] In particular, the probit specification

[1]See, for example, Pedersen et al. (1990), Brunello - Rizzi (1993), Hartog - Oosterbeek (1993), Dustmann - van Soest (1995), Bardasi (1996).

[2]See, for example, Rees - Shah (1986), Smeaton (1992).

[3]Another possibility is the adoption of a nested logit model which, however, allows

is found to be more appropriate than the logit one for the data we analyse, i.e. the Banca d'Italia Sample Survey on Budget of Italian Families (1993). In fact, the estimated correlation coefficients are significantly different from zero for both models we estimate for women and men respectively. The estimated correlation coefficients also have an economic interpretation in terms of correlation between utilities, that is "distance" between options. The strongly negative correlation coefficient we obtain - both for men and for women - implies a negative covariance between the utility of working in the private sector and the utility of working as a private employee, thus indicating the existence of profound differences between these types of workers.

Moreover, the results of logit and probit estimation exhibit substantial differences in terms of predicted probabilities and marginal effects of the explanatory variables, supporting the conclusion that it is important to adopt the more general probit formulation for multivariate choice models, while the zero covariance structure imposed by the logit formulation may be the source of misleading results.

The paper is structured as follows. Section 2 illustrates the theoretical underpinning for introducing the self-employedchoice as a third alternative and introduces the framework for empirical models on the sectoral choice in labour economics. Section 3 is devoted to the analysis of the identification and estimation problems characterizing multivariate probit models. Section 4 contains a description of the data and the model adopted, the results relative to the different steps needed for its estimation and, finally, an extended analysis and interpretation of the results obtained.

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for the estimation of only one covariance of the variance-covariance matrix, while the others are kept constrained to zero. The multinomial probit is therefore more general than the nested logit model.

2 Analysis of the sectoral choice

2.1 Theoretical aspects

Both neoclassical and non-competitive theories provide explanations of the allocation of heterogeneous workers to heterogeneous jobs. On the one hand, workers possess various skills and preferences, on the other hand, employers offer jobs that differ in skill content, security and working environment. The basic assumption made in a neoclassical framework is that workers try to maximize utility and not simply their monetary income; this means that they are interested in both the pecuniary and the non-pecuniary aspects of the job they perform. Now, jobs are different because some require more education and training, some are clean and others are dirty or dangerous, some require personal initiative and responsability and other are monotonous, some are secure from layoff and others are risky and strictly dependent on market conditions. All these job characteristics influence workers' utility and, as a consequence, individual choice.

One well-known job-matching explanation in a neoclassical framework is the "hedonic model" by Sherwin Rosen (1974), which accounts for the co-existence, in equilibrium, of different pairs of "type of worker-kind of job" at different wage levels. If the first implication of the model - that wages for more unpleasant jobs are higher - has been extensively criticized from a theoretical and an empirical perspective, the second implication - that workers with strong preferences for certain job characteristics will choose, in the absence of other constraints, the jobs with these characteristics, offered by the employers who most cheaply can generate them - is more uncontroversial.

In rejecting the functioning of a market clearing mechanism, dual labour market and segmentation theories emphasize the existence of queues in the "primary sector", but also in this case the theory is in perfect agreement with the observation of different workers allocated in different sectors.[4]

[4]For an overview of neoclassical and non-competitive models of segmented labour

The question we address here is if "sectors" - as these are defined according to the legal nature of the employer - can be treated as heterogeneous "jobs" with regard to the working conditions, place security, education and training required and the organisation of the activity so as to attract individuals with different tastes and characteristics. The purpose is not to test the validity of one theory vs. the other, but to make an empirical investigation of the features and the motivations which unite groups of individuals working for the same "type" of employer. The definition of "sector" adopted has allowed us to distinguish between three main status: private workers (individuals employed by a private employer), public workers (individuals employed by a public administration) and the self-employed (individuals working on their own account). The idea is that the classification in private, public and the self-employed sectors (i.e. on the basis of the nature of the employer) is at least as valid as the classification in productive sectors (i.e. on the basis of the nature of the product and/or the production process), becouse there exists a series of aspects that characterize them as different sectors..

In fact, the public sector characterizes, in Italy - at least up to now, the degree of job security (which is virtually complete), the level of education generally required (very high, particularly in some sub-sectors like those of health and the education)[5], the structure of the working hours in most subsectors (which offer a large amount of leisure and the opportunity of a collateral activity) and the social reputation of many occupations. On the other hand, the private sector leaves more scope for individual initiative and personal responsability and, thanks to greater mobility and flexibility, offers more possibilities for a career. Finally, self-employment can be singled out for the highest degree of independence that it offers in organizing working activity, and for the high level of autonomy in decision-making, even if this incurs a higher level of risk and income variability. It is therefore reasonable to assume that these

markets, see Lang-Dickens (1988).

[5]In the public sector the presence of blue-collar workers with a low level of education is much more limited than in the private sector.

different job characteristics and working environments attract individuals with different tastes and preferences, which are likely to be correlated with personal characteristics.

2.2 Empirical modelling

The usual way by which the choice of the sector is modelled is, in a neoclassical framework, by means of the individual utility function:

$$U_{ij} = U(W_{ij}, C_j) \tag{1}$$

where U_{ij} is the utility of individual i in sector j, W_{ij} is the corresponding wage and C_j are the characteristics of the working environment of sector j. Empirically, the model to be estimated is formulated as a latent variable model:

$$I_{ij}^* = \gamma_j' Z_{ij} + \varepsilon_{ij} \tag{2}$$

I_{ij}^* is a latent variable which may be interpreted as an indicator of the expected utility for individual i arising from choosing the j-th sector, $\gamma_j' Z_{ij}$ being the deterministic component[6] and ε_{ij} the random component of utility. Z_{ij} is a vector of individual specific explanatory variables influencing the sectoral choice and γ_j' is the corresponding vector of parameters to be estimated. Z_{ij} includes therefore all the variables expected to determine the earning opportunities and those related to the tastes and the individual preferences for the job characteristics. It is not possible to observe I_{ij}^*, but only its realization:

$$I = j \qquad iff \qquad I_{ij}^* > \max I_{ik}^* \qquad \forall k \neq j$$

i.e. the individual will choose sector j if the total utility associated with this choice is greater than the utility he/she would obtain in every other possible sector. In the above formulation the choice is depicted as a pure

[6]The $Z's$ variables are treated are non-stochastic, as it is usual to work conditionally on the regressors in this kind of models.

choice, i.e. possible rationing situations are ignored. Alternatively, a reduced form interpretation is possible, where supply and demand side effects mix and cannot be disentangled. In the latter case, what we observe, I_{ij} , is jointly generated by the behaviour of the worker, who tries to maximize his personal utility, and the imperfect functioning of the labour market, where queues at the entrance of certain sectors arise. The estimated coefficients of the explanatory variables therefore capture the joint effect of genuine preferences of the worker and employer's preferences as regards workers' characteristics.

The above reported model can easily be estimated using a multinomial logit model, which has the advantage of greater simplicity, but imposes very strong restrictions on the errors structure. In fact, the multinomial logit model is based on the assumption that errors ε_j are independently distributed with type I extreme-value distribution function,[7] which implies the validity of the Independence of Irrelevant Alternatives (IIA) property. This means that the utilities deriving from the three choices are mutually uncorrelated for the same individual, that is, the fact of getting a higher utility from choice j does not "tell" anything about the level of utility arising from any other alternative. This is unlikely to be true if certain characteristics of the sectors make two of them "closer", that is, more similar, than the third one. This is the reason why we have decided to estimate equation (2) using a multinomial probit model, which assumes that the error terms ε_j are distributed as a trivariate normal with covariance matrix Σ, in which any term outside the main diagonal can be different from zero (that is, correlation between utilities is allowed).

3 Identification and estimation in the multinomial probit model

There are several concerning the econometrics of the multinomial probit model which are non trivial and therefore make it worth reviewing before

[7] $F(\varepsilon_j) = \exp(-\exp(-\varepsilon_j))$.

applying it to real data. In this section, we start with a discussion of the theoretical and empirical identification aspects as emerge in the existing literature, focussing on the trivariate case. A brief review of the possible estimation methods is then presented, extending the reference to the general case involving more than three choices. Finally, we deal with the implementation of the estimation procedure in the trivariate case of interest, whose correct functioning is evaluated through a Monte Carlo experiment.

3.1 The identification problem

The trivariate probit model assumes that individuals select one of three mutually exclusive alternatives. The random utilities of individual i, $i = 1...N$, for choices 1,2,3 are formulated as:

$$\begin{aligned} u_{i1} &= \alpha_1 + \underline{x}_i'\beta_1 + \varepsilon_{i1} \\ u_{i2} &= \alpha_2 + \underline{x}_i'\beta_2 + \varepsilon_{i2} \\ u_{i3} &= \alpha_3 + \underline{x}_i'\beta_3 + \varepsilon_{i3} \end{aligned} \tag{3}$$

where: $\underline{x}_i$ is a $(k \times 1)$ vector of explanatory variables for individual i, which may contain both individual specific characteristics and alternative specific attributes faced by individual i; $\varepsilon_i = (\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3})'$ is a vector of stochastic terms which is assumed to be distributed as a trivariate normal, identically and independently across the N individuals, with zero mean and covariance matrix Σ:

$$\Sigma = Cov(\varepsilon_i) = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{pmatrix}$$

Arranging the parameters in (3) as $\alpha = (\alpha_1, \alpha_2, \alpha_3)'$, $\beta = (\beta_1', \beta_2', \beta_3')'$, the log-likelihood function associated with the model is:

$$L(\alpha, \beta, \Sigma) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{3} m_{ij} \ln P_{ij}(\alpha, \beta, \Sigma) \tag{4}$$

where $m_{ij} = 1$ if individual i chooses alternative j and $m_{ij} = 0$ otherwise, while $P_{ij} = \Pr(u_{ij} > u_{ik}, k \neq j = 1,2,3)$ represents the probability that individual i chooses alternative j and involves the evaluation of a bivariate integral in this three alternative case. Unfortunately, it is not possible to get unique maximum likelihood estimates of the parameters α, β, Σ in the above model, as it is not identified. Dansie (1985) gives the first systematic explanation of the identification problem in multinomial probit models and of its two sources. The first source of the identification problem is that the observed choices are only informative on the differences of the utilities and not on the utilities themselves. This means that in (4) all the probabilities of selection P_{ij} can be rewritten in terms of differenced utilities without altering the value of the log-likelihood function, for example:

$$\begin{aligned} u_{i1}^* &= u_{i1} - u_{i3} = \alpha_1^* + \underline{x}_i'\beta_1^* + \varepsilon_{i1}^* \\ u_{i2}^* &= u_{i2} - u_{i3} = \alpha_2^* + \underline{x}_i'\beta_2^* + \varepsilon_{i2}^* \\ u_{i3}^* &= 0 \end{aligned} \tag{5}$$

where $\alpha_l^* = \alpha_l - \alpha_3$, $\beta_l^* = \beta_l - \beta_3$, $\varepsilon_{il}^* = \varepsilon_{il} - \varepsilon_{i3}$, $l = 1,2$. As a consequence, the relevant distribution of the disturbances is not the above-mentioned trivariate one, but the bivariate distribution of $\varepsilon_i^* = (\varepsilon_{i1}^*, \varepsilon_{i2}^*)'$, which is normal with zero mean and covariance matrix Σ^*:

$$\Sigma^* = Cov(\varepsilon_i^*) = \begin{pmatrix} \sigma_{11}^* & \sigma_{12}^* \\ \sigma_{21}^* & \sigma_{22}^* \end{pmatrix}$$

with $\sigma_{lk}^* = E(\varepsilon_{il} - \varepsilon_{i3})(\varepsilon_{ik} - \varepsilon_{i3})$, $l,k = 1,2$. The second aspect of the identifiability of the model concerns the lack of information on the scale in the available data, i.e. u_{i1}^* and u_{i2}^* can be multiplied by an arbitrary constant without changing the value of the log-likelihood function. Therefore, in order to achieve identification, it is necessary to impose a restriction on Σ^*, and only two out of the three parameters of the bivariate covariance matrix are identified. The usual way of imposing this identification restriction is to standardize in order to have the first utility disturbance with unit variance, i.e. the utilities become:

$$u_{i1}^{**} = \frac{u_{i1}^*}{\sqrt{\sigma_{11}^*}} = \alpha_1^{**} + \underline{x}_i'\beta_1^{**} + \varepsilon_{i1}^{**}$$
$$u_{i2}^{**} = \frac{u_{i2}^*}{\sqrt{\sigma_{11}^*}} = \alpha_2^{**} + \underline{x}_i'\beta_2^{**} + \varepsilon_{i2}^{**} \qquad (6)$$
$$u_{i3}^{**} = 0$$

with $\alpha_l^{**} = \frac{\alpha_l^*}{\sqrt{\sigma_{11}^*}}$, $\beta_l^{**} = \frac{\beta_l}{\sqrt{\sigma_{11}^*}}$, $\varepsilon_i^{**} = \frac{1}{\sqrt{\sigma_{11}^*}}\varepsilon_i^*$, $l = 1, 2$, and:

$$\Sigma^{**} = Cov(\varepsilon_i^{**}) = \begin{pmatrix} 1 & \sigma_{12}^{**} \\ \sigma_{21}^{**} & \sigma_{22}^{**} \end{pmatrix}$$

with $\sigma_{lk}^{**} = \frac{\sigma_{lk}^*}{\sqrt{\sigma_{11}^*}}$, $l, k = 1, 2$.

With the above notation, the log-likelihood function of the identified model is written as:

$$L(\alpha^{**}, \beta^{**}, \Sigma^{**}) = \frac{1}{N}\sum_{i=1}^{N}\sum j = 1^3 m_{ij} \ln P_{ij}^{**}(\alpha^{**}, \beta^{**}, \Sigma^{**}) \qquad (7)$$

where, $P_{ij}^{**} = \Pr(u_{ij}^{**} \ > u_{ik}^{**},\ k \neq j = 1, 2, 3)$. We have, for example:

$$P_{i1}^{**}(\alpha^{**}, \beta^{**}, \Sigma^{**}) = \Pr(u_{i1}^{**} \ > u_{i2}^{**}\ ,\ u_{i1}^{**} \ > 0)$$
$$= \int_{-\infty}^{\frac{(\alpha_1^{**}+\underline{x}_i'\beta_1^{**})-(\alpha_2^{**}+\underline{x}_i'\beta_2^{**})}{\sqrt{1+\sigma_{22}^{**}-2\sigma_{12}^{**}}}} \int_{-\infty}^{\alpha_1^{**}+\underline{x}_i'\beta_1^{**}} \varphi(z_1, z_2; \rho_1)\ dz_1 dz_2 \qquad (8)$$

where $\varphi(z_1, z_2; \rho_1)$ is the bivariate normal density function of two random variables having zero mean, unit variance and correlation coefficient $\rho_1 = \frac{1-\sigma_{12}^{**}}{\sqrt{1+\sigma_{22}^{**}-2\sigma_{12}^{**}}}$. Similarly P_{i2}^{**} and P_{i3}^{**} can be derived.

The approach described above, consisting of working directly in a $J-1$ space (where, more generally, J is the total number of the alternatives), is recommended by Bunch (1991), who warns against the practice, quite often adopted in multinomial probit applications, of trying to achieve identification by imposing arbitrary normalizations and identification restrictions in the J space, for example, by setting some of the covariances equal to zero. Indeed, this can lead to invalid (i.e. non positive definite) covariance matrix in the $J-1$ space.

However, formulating the model according to the identification criteria outlined above does not completely solve the issue of its estimability. Keane (1992) notices that a formally identified multinomial probit model, i.e. a model specified as (7), can still be difficult to estimate as there exist a range of values of the parameters for which the log-likelihood function assumes different values all very close to its maximum. This case is referred to by Keane as *tenuous identification* and is likely to be a serious problem in multinomial probit applications whenever the model does not include some exclusion restrictions. As a matter of facts, the Keane's study should be considered as a ridefinition in the literature of the identification conditions for estimation of multinomial probit parameters. The lack of identificability arises from the fact that the effect of changes in the regression coefficients can be mimicked by changes in the parameters of the covariance matrix. This problem disappears if exclusion restrictions are introduced, i.e. if there are some alternative-specific attributes which enter as regressors only the utility function associated with one alternative and not the others. Keane shows through some simulation experiments that in the absence of exclusion restrictions, if the model is estimated by imposing some false constraint on the parameters, the corresponding maximized likelihood function does not suffer from a significant deterioration. Moreover, the parameter estimates exhibit big standard errors. These features disappear, however, in the presence of exclusion restrictions, as false constraints are rejected by appropriate likelihood tests and the parameters are estimated with satisfactory precision.

The above considerations on both the issue of formal identification and the necessity of putting forward a specification with exclusion restrictions have been kept in mind for the estimation of the trinomial probit model for the choice of the sector of occupation we present in section 4.

3.2 Estimation methods

As previously stated, the interest in the formulation of a probit specification for a multivariate choice model relies on the possibility of estimating the covariances among the error terms of the utility functions.[8] From the econometric point of view, however, the estimation of the probit model poses some difficulties due to the presence of multiple integrals in the likelihood function; more particularly, it contains integrals of the multivariate normal distribution whose dimension is equal to the number of alternatives *minus* one (see (8)). Because of this computational difficulty, most applied studies are based on the multinomial logit, despite the fact that the multinomial probit should be preferred for its greater generality in the specification of the covariance structure.

When the dimension of the integrals is no greater than four, corresponding to five alternatives in the model, numerical methods relying on different algorithms can be used to solve the multivariate normal integration problem which arises in the process of maximization of the likelihood function (see Pudney, 1988, Appendix 3 and Tong, 1990 for some surveys of these methods). This is the case in the three alternative probit models we consider in this paper, whose likelihood function involves bivariate normal integrals that can be evaluated numerically.

In order to cope with the general case in which the model under scrutiny postulates a series of alternatives higher than five, a number of methods based on simulation have been put forward in the literature. The existing simulation-based proposals for multinomial probit estimation can be grouped as follows: thoses which are based on classical estimation methods but use probability simulators, the Bayesian approach, and the Indirect Inference methodology. Geweke *et al.* (1994) compare the performance of some methods belonging to the first two groups through some Monte Carlo experiments, including the Simulated Method of Moments (McFadden, 1989 and Pakes and Pollard, 1989) and the Simulated Maximum Likelihood (Lerman and Manski, 1981) using the GHK (Geweke *et al.*, 1991) and Kernel Smoothing (Mc Fadden, 1989)

[8]Notice that the estimation of the additional parameters of the covariance matrix is theoretically possible to achieve without any constraint on the regressions of the utility functions. Moreover, the introduction of exclusion restrictions takes the form of the introduction of sector-specific variables which might be found to be important in the information set used for the specification of the utility functions.

probability simulators, and Bayesian Inference using Gibbs sampling (Mc Culloch and Rossi, 1994). Their main finding is that bayesian inference outperforms these two classical methods, while it is difficult to choose one out of the two classical procedures considered once the GHK probability simulator is adopted. As far as Indirect Inference is concerned, Gourieroux *et al.* (1993) suggest the use of a logit approximation as an auxiliary model for the estimation of the parameters of a multinomial probit formulation. The study of the performance of latter approach and its application to multivariate probit models is an interesting field for future research .

3.3 Assessing the estimation technique in the trivariate case

In order to achieve the estimation of the parameters of the trivariate probit model of section 4.3.2, a code has been built up in Gauss 3.2 which exploits:

a) the existing Gauss routine for the numerical computation of the bivariate normal integrals appearing in the log-likelihood function;

b) the maximization module "maxlik" for the numerical maximization of the trivariate probit likelihood function through the BHHH algorithm, which avoids the computation of second order derivatives and approximates the Hessian matrix by the negative of the outer product of the gradient.[9]

Given the complexity of the estimation problem, the correct functioning of the algorithm has in a first step been verified on simulated data, which was chosen in order for them to be generated as in Keane

[9]The gradient has been evaluated numerically. A subsequent check after the calculation of the analytical first order derivatives of the loglikelihood revealed that the accuracy of the numerical derivatives is very high. In fact, they coincide with the analytical ones up to the sixth decimal place.

(1992). This way, we obtain both a benchmark of the estimation procedure and the possibility of confirming the existence of the lack of identification already evidenced by Keane's results. Two different samples of 8,000 observations (Sample 1, Sample 2) have been generated according to the following identified model, with the exclusion restrictions $\beta_{13}^{**} = 0,\ \beta_{22}^{**} = 0$:

$$\begin{array}{l} u_{i1}^{**} = \alpha_1^{**} + \beta_{11}^{**}x_{1i} + \beta_{12}^{**}x_{2i} + \beta_{13}^{**}x_{3i} + \varepsilon_{i1}^{**} \\ u_{i2}^{**} = \alpha_2^{**} + \beta_{21}^{**}x_{1i} + \beta_{22}^{**}x_{2i} + \beta_{23}^{**}x_{3i} + \varepsilon_{i2}^{**} \end{array};$$

where:

$$\begin{pmatrix} \varepsilon_{i1}^{**} \\ \varepsilon_{i2}^{**} \end{pmatrix} \sim N.I.I.D.(\underline{0}, \Sigma^{**}), \qquad \Sigma^{**} = \begin{pmatrix} 1 & \sigma_{12}^{**} \\ \sigma_{21}^{**} & \sigma_{22}^{**} \end{pmatrix};$$

$x_{1i} \sim N.I.I.D.(6,5)$, x_{2i} and x_{3i} are dummies which assume the value 1 with probability 0.5.

Table 1 contains the results of the estimation procedure for both samples and the mean across the two in both the unrestricted case (i.e. when all the parameters are estimated) and when the model is estimated by imposing the exclusion restrictions $\beta_{13}^{**} = 0,\ \beta_{22}^{**} = 0$.[10] The crucial role of imposing some exclusion restrictions in order to get precise estimate of the parameters, as well as the reliability of the implemented estimation procedure, is apparent from the table. For example, it can be seen that in both the unrestricted cases the null hypothesis $\sigma_{12}^{**} = 0$ would be accepted, although the data have been generated from a process in which $\sigma_{12}^{**} = 0.9$. On the contrary, such a null hypothesis would be rejected in both the restricted cases.

[10] As starting values for the numerical maximization the true values have been used for simplicity. The numbers in brackets are the standard errors of the estimates evaluated using the outer product of the gradient.

Table 1. Simulation results.
Unrestricted and restricted estimations of the trivariate probit.
Two samples of 8,000 obs.

	True val.	**Sample 1**		**Sample 2**		**Mean**	
		Unres.	Res.	Unres.	Res.	Unres.	Res.
α_1^{**}	-0.80	-0.816 (0.063)	-0.792 (0.053)	-0.782 (0.063)	-0.739 (0.053)	-0.799 (0.063)	-0.766 (0.053)
β_{11}^{**}	0.20	0.160 (0.037)	0.211 (0.014)	0.173 (0.040)	0.194 (0.015)	0.167 (0.039)	0.203 (0.015)
β_{12}^{**}	-0.60	-0.715 (0.081)	-0.610 (0.050)	-0.746 (0.078)	-0.661 (0.045)	-0.731 (0.080)	-0.636 (0.048)
β_{13}^{**}	0	0.154 (0.093)	- -	0.078 (0.104)	- -	0.116 (0.099)	- -
α_2^{**}	-2.00	-2.002 (0.908)	-2.236 (0.285)	-4.341 (3.485)	-1.978 (0.263)	-3.172 (2.197)	2.107 (0.274)
β_{21}^{**}	0.40	0.372 (0.125)	0.438 (0.047)	0.716 (0.491)	0.397 (0.045)	0.544 (0.269)	0.418 (0.046)
β_{22}^{**}	0	0.053 (0.206)	- -	0.546 (0.745)	- -	0.300 (0.476)	- -
β_{23}^{**}	-0.60	-0.541 (0.268)	-0.625 (0.090)	-1.453 (1.171)	-0.664 (0.091)	-0.997 (0.719)	-0.645 (0.091)
σ_{22}^{**}	2.25	1.916 (1.464)	2.906 (0.796)	8.598 (13.164)	2.264 (0.583)	5.257 (7.314)	2.585 (0.522)
σ_{12}^{**}	0.90	0.472 (0.479)	1.189 (0.215)	0.381 (1.132)	0.845 (0.179)	0.426 (0.806)	1.017 (0.197)

4 A model of sectoral choice in Italy

4.1 The data

The data we use comes from the Banca d'Italia Sample Survey on the Budgets of Italian Families. This is a relatively unexploited data set, which contains information about the economic behaviour of Italian families at the microeconomic level. The basic survey unit is each member of a sampled family. In 1993 - the year of the last available data, which we are going to use - 8,089 families, corresponding to 24,013 individuals (14,395 income recipients), were included in the Survey. The objects of our analysis are the 7,688 individuals who were working on 31.12.1993. Personal data on each individual are recorded. These include sex, age, education (highest level of education attained), family relationship, marital status and the geographical area where the family lives. Data on participation in the labour market include the sector of activity (the production sector), the status (employee or self-employed worker) and the qualification (blue collar - white collar - manager). Besides education, Recorded human capital variables are total work experience[11] and seniority with the same employer, this latter variable representing a proxy for the specific human capital. The possibility of having access to a detailed personal section in addition to the data on wages and hours worked gives the Banca d'Italia Survey a great advantage over other sources such as ISTAT (Central Statistical Office) or INPS (National Institute for Social Security), which are perhaps more accurate in reporting the wages and hours worked, but which lack information on individual characteristics.

Each worker has been assigned to one of the sectors, private, public and self-employment, according to his main activity at end of 1993. Given that the Banca d'Italia questionnaire only records the main activity of the year as a whole (which is viewed as the prevailing activity since it has absorbed the greater number of the months in the year, the hours in the week, and so on), the precise activity of the worker on 31.12.1993 has been established by crossing several pieces of information reported in the sections recording each single source of income, in the section devoted to workers' mobility and in the introductory part, referring to the worker's personal characteristics. If for some individuals a degree of uncertainty about inclusion in one of the previously indicated categories might exist, in general the procedure adopted has proved quite reliable on the basis of all the controls carried out afterwards. In any case, the analysis of occupational status requires the researcher to fix one point in time and the most obvious choice for this seemed to be the end of the

[11] The total work experience is not directly recorded in the questionnaire but is approximated by subtracting the age at which the individual started working from his/her age at 31.12.1993. This is obviously a crude and imperfect measure of this variable (presenting moreover an asimmetry between men and women, given that women are more likely to interrupt their working career), but it is the best a researcher can do with the available data.

year. In Table 2 the distribution across the sectors of individuals, male and female, working at end of 1993 is presented.

Table 2. Distribution of the workers across the private, public and self.-empl. sectors.

	Private sector		Public sector		Self-empl.		Total
	No.	%	No.	%	No.	%	
Men	2320	46.74	1338	26.96	1306	26.31	4964
Women	1104	40.53	1070	39.28	550	20.19	2724
Total	3424	44.54	2408	31.32	1856	24.14	7688

Both "private" and "public" workers constitute the category of "employees", contrasting with the category of the "self-employed", singled out by the Banca d'Italia questionnaire. In the terminology of Banca d'Italia, "self-employed" is the broadest definition to indicate every kind of worker earning money from their own business, while "employee" indicates the worker who is paid by an employer. The public workers are the individuals working in one of the two productive sectors indicated in the questionnaire as clearly constituting the public area, those of "public administration" and "education and health", while the private workers constitute the remaining group.

4.2 The model and the choice of the explanatory variables.

In the model we are proposing, the individual can choose among three alternatives: 1) public employment, 2) private employment and 3) self-employment. As previously indicated, the choice of the sector is expected to be affected by relative earnings opportunities, by individual tastes for job characteristics and by personal attributes, which account for preferences and attitudes towards risk. One of the most obvious differences among the occupations in the three sectors is the degree of job stability and, therefore, the variance of expected earnings, self-employment no doubt being the most risky choice and public employment the least. Personal and family characteristics may be taken as proxies for the "desire for safety", and therefore for the attitute toward risk, as well as for individual preferences towards specific characteristics of the occupations. In the data set no choice specific variable appears, but it can be reasonably assumed that individual characteristics are correlated with tastes for job characteristics.

As proxies for "exposure to risk" the value of the total wealth owned by the family has been chosen. This variable - entering the model both linearly and squared - is supposed to capture the "degree of protection" enjoyed by the individual and therefore his willingness to take or to avoid the risks associated with certain occupations, in particular, with the self-employedsector. Other variables playing a similar role are the presence of other sources of income in the family, which means a diversification of risk, and of earnings other than income from the main activity earned by the worker himself, the number of income recipients, the marital status and role of the head of the family, these latter capturing the degree of family responsibilities. Personal characteristics such as age and level of education are obviously correlated with preferences for the working sector, while regional dummies are likely to capture the greater availability of jobs in certain sectors in specific areas.

Besides these personal characteristics, a macro variable has been added to the explanatory variables. This is the male or female (according to the gender of the worker) regional unemployment rate at the time the individual entered the sector in which he/she is currently working.[12] This demand-side variable captures the rationing level in the private sector and is therefore expected to significantly explain the entrance opportunities into this sector as well as into that of self-employment (insofar as it is a free-entry sector which the rationed individual may decide to enter in as a "second-best" solution) and possibly into the public sector. In this case,

[12]Notice that we do not know if, at the time of the last change, the individual entered the sector he/she is at the end of 1993 coming from a different one or simply changing job inside the same sector. However, we think that this makes little difference, given that in any case a new job has been found; in other words, the unemployment rate is expected to have the same influence on job opportunities, independently of the history of the worker, and, more precisely, independently of the sector the individual moved from.

on the one hand, the government may react to unfavourable economic situations by offering additional jobs in the public administration, on the other the queues at the entrance into this sector may increase. Moreover, because it is a pure demand-side variable, the regional unemployment rate at the time of entry into the working sector partly disentangles the age effect - i.e. of changing preferences as age changes - from cohort effects due to the changing economic background for the different groups of workers entering the labour market and the working sector at different times.

The series of regional unemployment rates for men and women have been taken from Annuario Statistico and Annuario delle Statistiche del Lavoro by ISTAT. Unfortunately, the regional unemployment rate by sex is regularly available only from 1967 on and for the single years 1952, 1954, 1962, 1963 before that. Given that many individuals in the sample have tenure which is longer than 25 years at end of 1993, we have decided to construct the unemployment rate for the missing years from 1952 to 1967 by linear interpolation[13]. We think that this solution presents fewer drawbacks relative to the alternative one of dropping hundreds of older workers from the sample, given that in the '50s and the '60s the unemployment rate was quite low everywhere in Italy, with few variations in time. Once the series 1952-1993 of the regional unemployment rate have been added to the other variables, only a few individuals are excluded from the original samples. In Table 3 the actual sample sizes used for the estimation of the model are reported.

[13]We have not extrapolated the regional unemployment rate before 1952 because we have only one point in time on which rely (1952) and also because the missing years represent in this case the immediate post-war period, which can certainly be said to be anomalous for various reasons.

Table 3. Actual sample sizes

	Private sector		Public sector		Self-empl.		Total
	No.	%	No.	%	No.	%	
Men	2278	47.56	1323	27.62	1189	24.82	4790
Women	1084	40.86	1053	39.69	516	19.45	2653
Total	3362	45.17	2376	31.92	1705	22.91	7443

By comparing these figures with thoses reported in Table 2, we can see that the few excluded individuals are almost all self-employed. Moreover, they are obviously all older workers. This small alteration of the sample is justified by the great advantage of using the regional unemployment rate as an extra macro-variable in the estimation.

Finally, what we need is a sector-specific variable to solve the problem of tenuous identification illustrated in paragraph 3.1. The solution adopted is presented in the following section.

4.3 Model estimation

4.3.1 Sector specific variable construction

The nature of the problem with which we are dealing as well as the kind of data available imply a model including individual-specific variables only. Therefore, difficulties arise in finding alternative-specific variables, which, on the contrary, would naturally exist in, for example, transportation-choice models. In order to overcome these difficulties, we have decided to "create" one sector-specific variable (i.e. a variable taking two different values for each of the two sectors)[14] each of these values entering a different choice equation.

As a possible solution Heckman-Sedlacek (1985) propose the choice of other personal non-labour income, which they estimate as a function of

[14]Given the way the identification problem has been solved, we need only two different values of the choice-specific variable and not three.

individual characteristics for each sector.[15] They interpret this variable as a proxy for the "collateral benefits" of being in a specific sector. On the one hand, the other personal non-labour income is expected to enter the preference function directly; on the other, it also makes sense to assume that each sector offers different opportunities to generate a certain amount of other personal non-labour income. In particular, Heckman and Sedlacek, who refer to the U.S. labour market, interpret non-labour income as all non-employment income, including unemployment benefits and social transfers, underlining the fact that entitlements to various social programs are conditional on sectoral participation.

A better solution seems to us the choice of predicted earnings. This variable has an obvious, more direct interpretation, given that it is one of the most important determinants of the utility of choosing one specific sector. The problem is that, as for non-labour income, the "potential wage" in each sector for every individual is not observable; we observe only the actual earnings in the sector chosen. Therefore, we have to estimate it.

The estimation of sectoral earnings is affected by selection bias, due to the fact that the groups of workers we observe in each sector are not random samples of the population, but selected samples of individuals who have chosen the sector they are in by maximizing their utility, to which the wage gives an important contribution. The estimation of the predicted wages has consequently been made by adopting a two-step procedure, in which, at the first step, the choice of the sector is explained and the correction factors computed and, at the second step, a regression of wage on human capital explanatory variables and the correction factors is carried out. The model used is that developed in Bardasi (1996). A multinomial logit model has been used at the first step to explain the sectoral choice among self-employment, private and public sectors. Even if this is a second-best solution (the Hausman test has shown that the

[15] In other words, they regard each sector as "paying" in a different way all the personal characteristics which are useful in producing extra-income, in addition to the "official wage" earned in that sector. The sectors they refer to are the manufacturing, mon-manufacturing and non-market sectors.

IIA property does not hold in this case and, by consequence, that the multinomial logit model is not the most appropriate model), it is nevertheless a feasible starting point, given the need of correcting for selection bias in some way. The problems in estimating self-employment earnings, besides private and public wages, are easily avoided given that only two alternative-specific variables are needed (one of the three utilities, in the present case the utility of choosing self-employment, is set to zero for identification reasons).

The results are reported in Tables A.1, A.2 and A.3 in the Appendix. Tables A.1 and A.2 report the results of the multinomial logit models and Table A.3 of the wage regressions. Two different specifications have been found for the two sectors, private and public, as the most appropriate ones, both for the multinomial logit model and for wage regressions. Moreover, a separate analysis has been carried out for men and women, given that the behaviour of the two genders is expected to be considerably different in terms of choice of the working sector.

The dependent variable in the wage equations is the logarithm of the "hourly wage in the main sector earned in year 1993". The explanatory variables are the typical human capital variables (education level, tenure with the present employer, experience before the present job), the geographical and sectoral dummies and the interaction terms between all these explanatory variables and a dummy for blue collars, in order to obtain separate coefficients for blue and white collars, given the different composition in terms of occupational groups in the two sectors.

On the basis of the estimated wage regressions, the predicted wages for every individual in the public and the private sector have been estimated. The predicted wages in the two sectors have been included as choice-specific regressors in a second multinomial logit model, whose estimation (step 1 of next section) is aimed at obtaining initial values for the estimation of the multinomial probit model. The estimates are reported in Table A.5 and A.7 of the Appendix.

4.3.2 Probit estimates

The probit model is specified as described in (3.1) and includes the sector specific variables obtained in the previous section in order to insert some exclusion restrictions which are necessary for identification. Two separate models have been estimated for women (2653 observations) and men (4790 observations). In both cases, the estimation has been carried out according to the technique illustrated in section (3.3) and involves the following three steps.

1. **Derivation of the logit estimates of a three choice model.** This stage, which presents the advantage of an automatically implemented estimation procedure, is essential for the derivation of a sensible starting value for the numerical estimation of the parameter vector of the probit model in the following step. The utility structure underlying the trivariate logit model is the same as the probit one (see section (3.1)), i.e. we can write: $u^l_{ij} = \gamma_{j+}\underline{x}'_i\delta_j + \eta_{ij}$, $j = 1,2,3$, where identification requires some normalization, for example $\gamma_3 = 0$, $\delta_3 = \underline{0}$. However, the logit model differs from the probit one in as far as the distribution of the error terms is concerned. While the probit model postulates the normal distribution of the errors, in the logit case, the error terms in the original model are assumed to be type 1 extreme value distributed. This distributional assumption has three important consequences: firstly, the variance of the differenced error terms, which have logistic distribution, is equal to $\frac{\pi^2}{3}$ (and therefore such error terms have the same variance); secondly, their covariance is forced to be zero, thirdly, the probability that person i will choose sector j, P^l_{ij}, is characterized by a different functional form, namely$P^l_{ij} = \frac{\exp(\gamma_j+\underline{x}'_i\delta_j)}{\sum_s \exp(\gamma_s+\underline{x}'_i\delta_s)}$, $j,s = 1,2,3$.

2. **Estimation of the trivariate probit with restricted covariance.**
   This intermediate step consists in estimating the probit analogous to the logit formulation above. This is achieved by restricting the

covariance matrix of the probit error terms (Σ^{**} in section (3.1)) to be the identity matrix, i.e. by imposing unit variance on both errors and zero covariance ($\sigma_{11}^{**} = \sigma_{22}^{**} = 1$, $\sigma_{12}^{**} = 0$). The logit estimates can then be used as starting values for the numerical procedure described in (3.3) after the transformation which makes logit and probit coefficients comparable in this case. Stern (1989) generalizes the Amemya's 1.6 rule (1981)[16], valid for comparison of the coefficients of bivariate logit and probit models, to multinomial models with independent errors. Accordingly, we have adopted the comparison factor he suggests for the three-choice case, say $b_3 = 0.55698$,[17] and we put: $\alpha_j^{**(0)} = \widehat{\gamma}_j b_3$, $\beta_j^{**(0)} = \widehat{\delta}_j b_3$, $j = 1, 2$, where the subscript (0) indicates the initial values used to implement the numerical maximization of the probit loglikelihood. The resulting probit estimates allow for an evaluation of the effect of the different assumed functional form on the estimated coefficient of the variables, without including the effect of relaxing the covariance structure.

3. Estimation of the trivariate probit model with unrestricted covariance.

The ultimate aim of the estimation procedure is to relax the constraint $\sigma_{12}^{**} = 0$, in order to exploit the advantage in terms of covariance pattern flexibility offered by the probit specification. This last estimation is performed by adding the covariance parameter to the previous probit parameter vector and using the probit estimates obtained at step 2) as starting values (for the covariance parameter we put $\sigma_{12}^{**(0)} = 0$). Although in principle we could estimate the variance σ_{22}^{**} as well, we proceeded gradually in the generalization

[16] According to this rule the logit coefficients multiplied by 1.6 are comparable with the probit ones in the bivariate case.

[17] This value is obtained by dividing the a_3 comparison factor in Stern's notation by $\sqrt{2}$, as its notation refers to the error terms of the original models, while the models are expressed in the differences of the error terms, whose variance is two times the variance of the original model error terms.

of the model, and kept the scale restriction $\sigma_{22}^{**} = 1$.[18] This implies that we are in fact estimating the correlation between the two normalized utilities, say ρ_{12}^{**}. In order to achieve the estimation of ρ_{12}^{**}, it was essential to impose the constraint that the correlations $(\rho_1, \ \rho_2, \ \rho_3)$ in the three bivariate normal distributions under integration in the loglikelihood function (cf. (8)) be less than one in modulus. This is easily accomplished when $\sigma_{22}^{**} = 1$. Given that in this case we have: $\rho_1 = \frac{1-\sigma_{12}^{**}}{\sqrt{2-2\sigma_{12}^{**}}}$, $\rho_2 = \rho_1$, $\rho_3 = \rho_{12}^{**}$, the maximization can be performed with respect to ρ_3 and by imposing it to be less than one in modulus.[19]

Tables A.5 to A.8 of the Appendix display the results corresponding to the above first two steps for the two models (men and women), while Table 4 and Table 5 contain the unconstrained covariance probit results.[20] The reported standard errors of the probit estimates are the heteroscedasticity consistent, i.e. the diagonal elements of the matrix $\widehat{J}_T^{-1}\widehat{I}_T\widehat{J}_T^{-1}$, where $\widehat{I}_T$ is the outer product of the gradient, evaluated analytically, and $\widehat{J}_T$ is the negative Hessian matrix, evaluated numerically. The analytical expression of the first order derivatives of the probit loglikelihood with respect to the parameters is obtained in the same way as indicated in Appendix A.4 for the marginal effects of the continuous variables.

An inspection of the Tables reveals some important facts. First, the predicted wage sector specific variables are strongly significant in both the estimated logit and probit. This confirms the theoretical importance of including these sector-specific variables in the information set, leaving

[18]The attempt to release this scale restriction was unsuccessful, despite various trials with different numerical maximization algorithms. The estimated parameter vector got stuck very close to the starting value (with $\sigma_{22}^{**} = 1$), without reaching the convergence in 100 iterations.

[19]The constraint is imposed through the reparametrization: $\rho_3 = \frac{1-e^r}{1+e^r}$.

[20]For computational reasons the variables age2, otherfi2 and otherpi2 have been rescaled by dividing by 1000.

the need for them to the probit estimation to one side. Second, it can be remarked that the separate effect of a different functional form is not negligible. Tables A.5 and A.6, and Tables A.7 and A.8 do in fact differ as far as the significance of some regressors is concerned. Further differences in the regression coefficients also appear in the comparison between Table A.6 and 4, and Table A.8 and 5 respectively, corresponding to the effect of releasing the constraint $\rho_{12}^{**} = 0$. These changes are commented on and interpreted in more detail in the following section. It can be observed that the estimated correlation between the two normalized utilities has a high negative value and is fairly significant in both women and men models. This means that the hypothesis of IIA is rejected by our data. The inadequacy of imposing a zero correlation is confirmed by the loglikelihood ratio for the test on the restriction $\rho_{12}^{**} = 0$. Denoting by $\widehat{l}^{w}$ the estimated unrestricted loglikelihood and by $\widetilde{l}^{w}$ the restricted one for women, and with $\widehat{l}^{m}$ and $\widetilde{l}^{m}$ the same quantities for men, we have:

$$LR^{w}_{(\sigma_{12}^{**}=0)} = 2(\widehat{l}^{w} - \widetilde{l}^{w}) = 55.38$$
$$LR^{m}_{(\sigma_{12}^{**}=0)} = 2(\widehat{l}^{m} - \widetilde{l}^{m}) = 186.55$$

which, confronted with the critical value $\chi^2_{(1,0.05)} = 3.84$, highlights the significant increase in the loglikelihood obtained by releasing the covariance parameter in both cases.

Table 4. Unconstrained covariance probit estimates.[21] Men

Log likelihood=-3713.80, 4790 obs.

Stars denote unsignificance at 5% level.

Variable	Coeff.	S.E.		Coeff.	S.E.
Private			*Public*		
age	0.1921	0.0177		0.0790	0.0161
age2/1000	-2.010	0.1990		-0.7700	0.1864
educ2	0.1922	0.0675		0.4763	0.0714
educ3	0.7631	0.0872		0.2855	0.0864
educ4	0.2135*	0.1325		0.2169*	0.1729
North-West	0.8446	0.0731		-0.4947	0.0729
North-East	0.6379	0.0740		-0.3959	0.0735
Centre	0.3624	0.0666		-0.1714	0.0638
otherfi	0.0040	0.0017		0.0048	0.0018
wealth	-0.6721	0.1410		-1.1916	0.1445
wealth2	0.0689	0.0345		0.0955	0.0141
house	0.0944*	0.0531		0.1950	0.0537
nrecip	0.0139*	0.0344		-0.1326	0.0371
otherpi	0.0172	0.0026		0.0040*	0.0027
otherpi2/1000	-0.3221	0.0228		-0.0200*	0.0252
runrate	-6.2733	0.9550		2.7385	0.9532
pwagepr	-33.4478	1.6529			
pwagepr2	6.0308	0.3192			
pwagepu				4.4792	2.2099
pwagepu2				-0.4880*	0.4349
constant	40.4622	1.9298		-10.5067	2.7610
ρ_{12}^{**}				-0.9531	0.0165

[21] **The outcome self-employment is the comparison group.**

Table 5. Uncostrained covariance probit estimates. Women

Log likelihood=-1903.33, 2653 obs.

Stars denote unsignificance at 5% level.

Variable	Coeff.	S.E.		Coeff.	S.E.
Private			*Public*		
age	0.0540	0.0239		0.1381	0.0234
age2/1000	-0.8339	0.2938		-1.4533	0.2846
educ2	-0.0934*	0.0941		0.4276	0.1124
educ3	-0.0550*	0.1162		1.1054	0.1624
educ4	-0.1857*	0.2105		0.6166	0.2759
married	-0.2387	0.0829		-0.1441*	0.0854
North-West	0.9199	0.1139		-0.5068	0.1124
North-East	0.6782	0.1151		-0.4930	0.1131
Centre	0.6160	0.1048		-0.3688	0.1007
otherfi	0.0081	0.0033		0.0078	0.0031
otherfi2/1000	-0.0409	0.0192		-0.0255*	0.0185
wealth	-0.7030	0.1869		-1.3060	0.1725
wealth2	0.1004	0.0266		0.1371	0.0311
house	0.0497*	0.0764		0.2420	0.0778
nrecip	-0.0332*	0.0463		-0.1354	0.0455
otherpi	0.0490	0.0110		-0.0009*	0.0085
otherpi2/1000	-0.7474	0.2450		0.0540*	0.0909
pwagepr	-11.3891	1.7656			
pwagepr2	1.9119	0.3875			
pwagepu				-16.3414	2.7955
pwagepu2				3.6323	0.5784
headfam	-0.4310	0.1175		0.0924*	0.1224
runrate	-2.2180	0.5798		-1.3808	0.5727
constant	14.9424	1.9844		14.9858	3.4443
ρ_{12}^{**}				-0.8326	0.0452

4.4 Interpretation of results

4.4.1 Comparison between logit and probit estimates

As a first indicator of the performance of the model, we have chosen to tabulate the actual choices versus the predicted choices. On the basis of the predicted probabilities of being in one of the three sectors, we have placed the individual in that for which the predicted probability was the highest. The results are reported in the Tables 6 and 7, while Table 8 reports some indices which are useful in summarizing the results. In these, we are comparing the multinomial logit model and the unconstrained multinomial probit. The two models do not differ much under the profile of the allocation of the workers across the three sectors on the basis of the above reported procedure.[22]

Table 6. Performance of the logit model

	MEN				WOMEN			
Observed \ Predicted	priv.	publ.	s.e.	tot.	priv.	publ.	s.e.	tot.
priv.	1869	280	129	2278	832	220	42	1084
publ.	533	678	112	1323	279	719	55	1053
s.e.	304	287	598	1189	110	125	281	516
tot.	2706	1245	839	4790	1221	1054	378	2653

[22]It is worth considering that, even when the predicted probabilities generated by the two models differ considerably, the allocation of the worker in one of the three sectors does not vary unless the change in the probabilities is big enough to modify their ranking (for example, from Pr(PU)>Pr(PR)>Pr(SE) generated by the logit to Pr(PR)>Pr(PU)>Pr(SE) generated by the probit). This is why the tabulation "observed vs. predicted cases" is only one possible but imperfect measure of the performance of the two models.

Table 7. Performance of the probit model

Observed \ Predicted	MEN				WOMEN			
	priv.	publ.	s.e.	tot.	priv.	publ.	s.e.	tot.
priv.	1842	250	186	2278	833	197	54	1084
publ.	521	641	161	1323	278	709	66	1053
s.e.	283	228	678	1189	106	115	295	516
tot.	2646	1119	1025	4790	1217	1021	415	2653

The unconstrained multinomial probit allocates more easily the workers in the category "self-employment" than the multinomial logit model and this is reflected both in the higher percentage of self-employed classified as self-employed and in the lower rate of predicted self-employed who are actually self-employed (indicating that the increase of the former percentage is made, at least in part, at the expenses of a higher number of mistakes). However, we think that the increase in the easiness in predicting self-employment should be regarded as a positive feature given that this is one option with a low rate of cases correctly classified.[23]

Table 8. Comparison of the performance of logit and probit models.

	MEN		WOMEN	
	logit	*probit*	*logit*	*probit*
% of private classified private	82.05	80.86	76.75	76.84
% of public classified public	51.25	48.45	68.28	67.33
% of self-empl. classified self-empl.	50.29	57.02	54.46	57.17
% of tot. obs. correctly classified	65.66	65.99	69.05	69.24
% of predicted private actually private	69.07	69.61	68.14	68.45
% of predicted public actually public	54.46	57.28	68.22	69.44
% of predicted self-empl. actually self-empl.	71.27	66.15	74.34	71.08

[23] Another control of the performance of the two models has been carried out by comparing the probabilities predicted by the logit and the probit for the actual status of the worker. In the large majority of the cases the probit model generates a higher predicted probability of being in the sector the worker is actually in than the logit model.

More interesting is to compare the marginal effects and the elasticities of the explanatory variables. Both for the multinomial logit and the unconstrained multinomial probit, we have computed and indicated separately the "direct" and the "total" effects of a change of one continuous explanatory variable on the probability of entering either one or the other sector.[24]

As explained in more detail in Appendix A.1, the "direct" effect does not take into account the change in the probability due to the variation of the predicted earnings, when the explanatory variable in question also enters the wage regressions and/or the first multinomial logit which is used to compute the selection bias, while the "total" effect does. In Tables 9 through 12 the marginal effects and the elasticities for the multinomial logit model and the unconstrained ($\rho \neq 0$) multinomial probit model are shown. The differences between the two models are now clearer.

Table 9. Marginal effects and elasticities. Logit model, Men.

	Direct effect				Total effect			
Variable	P(private)		P(public)		P(private)		P(public)	
	M. eff.	Elast.	M. eff.	Elast.	M. eff.	Elast.	M. eff.	Elast
age	0.0040	1.4745	0.0018	0.1264	0.0010	0.3640	0.0041	0.2824
oth. fam. inc.	0.0004	0.0689	0.0040	0.1348	0.0006	0.1137	0.0039	0.1312
oth. per. inc.	0.0016	0.1137	0.0027	0.0361	0.0036	0.2557	0.0014	0.0185
family wealth	-0.0376	-0.0939	-0.6950	-0.3231	-0.1114	-0.2777	-0.6559	-0.3052
unempl. rate	-1.2429	-1.3848	0.6025	0.1248	-1.3833	-1.5409	0.6868	0.1421
lnwagepr		-0.5470		0.3551				
lnwagepu		-0.1209		0.4730				

[24]The marginal effects and elasticities have been computed in correspondence of the vector of regressors identifying the "average" individual given in Appendix A.4.

Table 10. Marginal effects and elasticities. Probit model, Men.

	Direct effect				Total effect			
Variable	P(private)		P(public)		P(private)		P(public)	
	M. eff.	Elast.	M. eff.	Elast.	M. eff.	Elast.	M. eff.	Elast
age	0.0065	2.0298	0.0069	0.5093	0.0019	0.6059	0.0075	0.5567
oth. fam. inc.	0.0008	0.1288	0.0019	0.0687	0.0012	0.1929	0.0020	0.0719
oth. per. inc.	0.0025	0.1537	0.0015	0.0208	0.0057	0.3438	0.0014	0.0198
family wealth	-0.1310	-0.2808	-0.4523	-0.2249	-0.2518	-0.5396	-0.4708	-0.2341
unempl. rate	-1.2954	-1.2366	1.0867	0.2408	-1.5195	-1.4506	1.0724	0.2376
lnwagepr		-0.8610		0.0002				
lnwagepu		-0.0001		0.8105				

Table 11. Marginal effects and elasticities. Logit model, Women.

	Direct effect				Total effect			
Variable	P(private)		P(public)		P(private)		P(public)	
	M. eff.	Elast.	M. eff.	Elast.	M. eff.	Elast.	M.. eff.	Elast
age	-0.0031	-1.0867	0.0041	0.1884	-0.0049	-1.7171	0.0056	0.2587
oth. fam. inc.	0.0001	0.0538	0.0013	0.0614	0.0002	0.0764	0.0012	0.0581
oth. per. inc.	0.0053	0.0833	-0.0018	-0.0037	0.0053	0.0832	-0.0018	-0.037
family wealth	0.0276	0.0736	-0.2391	-0.0846	0.0120	0.0319	-0.2234	-0.0791
unempl. rate	-0.0958	-0.1054	-0.2671	-0.0390	-0.0793	-0.0872	-0.2769	-0.0405
lnwagepr		-0.2280		0.2101				
lnwagepu		-0.1974		0.3236				

Table 12. Marginal effects and elasticities. Probit model, Women.

	Direct effect				Total effect			
Variable	P(private)		P(public)		P(private)		P(public)	
	M. eff.	Elast.	M.. eff.	Elast.	M. eff.	Elast.	M. eff.	Elast
age	-0.0030	-0.8308	0.0077	0.3819	-0.0062	-1.7369	0.0080	0.3950
oth. fam. inc.	0.0006	0.1673	0.0013	0.0649	0.0007	0.1915	0.0012	0.0614
oth. pers. inc.	0.0082	0.1033	-0.0024	-0.0053	0.0082	0.1033	-0.0024	-0.0053
family wealth	-0.0554	-0.1183	-0.2917	-0.1103	-0.0800	-0.1706	-0.2806	-0.1061
unempl. rate	-0.3258	-0.2868	-0.2574	-0.0402	-0.2901	-0.2554	-0.2455	-0.0383
lnwagepr		-0.3813		0.1027				
lnwagepu		-0.1107		0.6117				

It can be seen that the two models produce elasticities that differ considerably in both the size and, sometimes, the sign. See, for example the "total" elasticity of age for men and of wealth for women. The unconstrained multinomial probit, moreover, produces, in general, greater marginal effects and elasticities than the multinomial logit. A comparison between the direct and the total elasticities shows the importance of taking into account any additional effect of the same variable that - via the predicted wages - may compensate or amplify the magnitude of the direct derivative. Differences between the multinomial logit and the multinomial probit model are also evident as far as the dummies are concerned. In this case, to measure the effect of the categorical variables, one dummy has been changed - in turn - keeping all the other characteristics fixed at their average level. The results are reported in Tables 13 and 14. The variations are noticeable, especially for men, and for some variables (see, for example, the change in probabilities due to all levels of education - especially that of the degree - and to the variations in the composition of the family as far as the "active" members are concerned, for men, and to primary education, to house ownership and to marital status, for women).

Table 13. Changes in probabilities due to changes in the categorical variables. Men.

Variable	Logit			Probit		
	P(priv.)	P(publ.)	P(s.e.)	P(priv.)	P(publ.)	P(s.e.)
average individual	0.1076	0.5793	0.3131	0.1257	0.5416	0.3327
no educ.-prim. educ.	0.0877	0.3790	0.5333	0.0903	0.3550	0.5547
high school	0.2426	0.5075	0.2499	0.2820	0.4653	0.2527
degree	0.1707	0.3768	0.4525	0.1301	0.4384	0.4315
1 income recipient	0.0985	0.6439	0.2576	0.1228	0.5937	0.2835
3 income recipient	0.1155	0.5112	0.3733	0.1286	0.4888	0.3827
North West	0.2970	0.3636	0.3394	0.3809	0.3479	0.2712
North East	0.2376	0.3947	0.3677	0.3053	0.3853	0.3094
Centre	0.1717	0.5171	0.3112	0.2163	0.4733	0.3104
House not owned	0.1032	0.4703	0.4265	0.1072	0.4639	0.4289

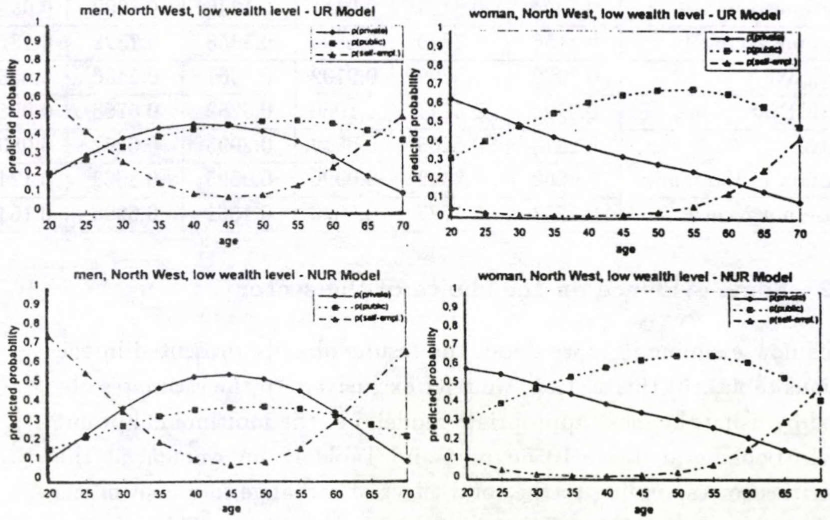
Table 14. **Changes in probabilities due to changes in the categorical variables. Women.**

Variable	Logit			Probit		
	P(priv.)	P(publ.)	P(s.e.)	P(priv.)	P(publ.)	P(s.e.)
average individual	0.1091	0.8211	0.0698	0.1362	0.7688	0.0950
compulsory educ.	0.1759	0.5542	0.2699	0.1461	0.5417	0.3122
primary educ.	0.2248	0.3737	0.4015	0.1707	0.3749	0.4544
degree	0.1395	0.7085	0.1520	0.1249	0.6148	0.2603
non married	0.1174	0.8483	0.0343	0.1689	0.7872	0.0439
1 income recipient	0.1024	0.8435	0.0541	0.1346	0.8002	0.0652
3 income recipient	0.1156	0.7949	0.0895	0.1358	0.7322	0.1320
North West	0.3909	0.5299	0.0792	0.3961	0.5456	0.0583
North East	0.3196	0.5744	0.1060	0.3282	0.5768	0.0950
Centre	0.2815	0.6266	0.0919	0.2995	0.6202	0.0803
headfam of the family	0.0662	0.8342	0.0996	0.0695	0.8063	0.1242
House not owned	0.1253	0.7727	0.1020	0.1361	0.6996	0.1643

4.4.2 Some evidence on the choice of the sector

Let us now examine in more detail the results already presented in the previous tables. In this section, we refer exclusively to the estimates obtained by using the most appropriate model, i.e. the multinomial probit model. Looking at Table 10 for men and Table 12 for women, at the elasticities corresponding to the total effect of a change in a continuous variable, the strong effect of the age variable is evident. This effect is clearly negative for the probability of being in the private sector as far as female workers are concerned, while it is moderately positive for men. Together with the positive elasticities of the probabilities of being in the public sector, both for men and for women, this contributes to a negative elasticity of the probability of being self-employed with respect to age for both genders, which is especially strong for men and almost close to zero for women. This result may appear counter-intuitive; we would expect to observe younger workers entering more easily into the private sector and moving to self-employment as physical and human capital are accumulated. However, the elasticities we have computed cannot be compared with the frequencies observed in the various sectors at different age levels.[25] In fact, they are computed for a specific type of individual, i.e. they represent the effect of changing age, keeping fixed all the other characteristics at the "average" type.

In order to gain more insights about the effect of age on the probability of being in a certain sector, we have depicted the predicted probabilities for specific types of individuals. In Figure 1 the case is presented of a man and a woman living in the North-West of Italy with a low wealth level (100 million Lit.) and at an unemployment rate of 12%.



The two graphs at the top are drawn on the basis of the coefficients estimated using the probit model presented in the preceeding sections (let us call this model UR). The two graphs at the bottom refer to the same model in which, however, the regional unemployment rate has not been included among the regressors (let us call this model NUR).[26]

[25]The hystograms - not reported here - representing the sector partecipation frequencies by age display for both genders a trend which is monotonously decreasing in the private sector and monotonously increasing in the self-employment. In the public sector it is increasing until 40 for men and 33 for women, then it remains, more or less constant, to begin decreasing after 60.

[26]These estimates have been obtained in a preliminary phase of this study. They are not reported here, but are available on request.

It can be observed that in the case of men both graphs can be vertically "split" into two parts. In the last 20-25 years of the life-cycle the probabilities follow the "expected" pattern, i.e. the probability of being in the private sector decreases and that of being self-employed increases. However, in the first 20-25 years this pattern is reversed. Interestingly, the graph derived from the NUR model displays more pronounced curvatures of the private and self-employment profiles than those derived from the UR model. Moreover, in the graphs based on the UR model the overall level of the predicted probabilities also changes.

The graphs referring to the male worker show the effect of the regional unemployment rate at the time of entering the sector. When using a cross-section, in fact, the variations in the probability of being in a sector as age varies also incorporate cohort effects and capture macroeconomic events and policy interventions which have affected the size of the sector in specific periods. In the case of the average man, the increase in the probability of being in the private sector as age increases, or rather, the decrease of this probability as age decreases, is amplified by the increase of the unemployment rate for the youngest cohorts, particularly at low education levels, as the graphs drawn on the basis of NUR model (which does not take into account the variation of the unemployment rate for different cohorts) demonstrate. Accordingly, the probability of being self-employed increases when the individual is younger also because self-employment is the only possible alternative in such a situation. Once the regional unemployment rate is taken into account, part of this cohort effect disappears. Obviously, the variation in the regional unemployment rate is only one of the possible elements introducing cohort effects, even if, we think, it is a very important one. It is interesting to notice that the younger workers are with higher and increasing probabilities self-employed, even when accounting for the regional unemployment rate. This may reflect the general trend recorded in many European countries of increasing self-employment rates; in Italy, specific incentives for young entrepreneurs have been introduced in the last few years, representing another explanation for the increasingly common attitude of looking at self-employment as a possible first job instead of final one.

In the case of women, as opposed to man, the introduction of the regional unemployment rate does not produce significant changes in the pattern of the predicted probabilities by age. In fact, in both the UR and the NUR models female workers show behaviour that is more similar to that which has been indicated as intuitive, with decreasing predicted probabilities of being in the private sector and increasing predicted probabilities of being self-employed on the whole age range. In this case, the introduction of the regional unemployment rate does not modify the coefficient of age to any significant degree. A possible explanation for this could be connected with the increase in the participation of women to the labour force. Even if the female unemployment rate has considerably increased and now reaches levels which are in all regions on average twice the corresponding figure for men, it is also true that the private sector has hired an increasing number of women.[27] Therefore, the probability that a woman aged 20 is in the private sector is higher than that of a woman aged 30, even when the variations of the unemployment rate are not taken into account, as in the NUR model. We can also notice that, for the youngest female worker, some slightly increasing predicted probabilities of being self-employed as their age decreases are observed. It might be that, as regards the choice of self-employment, women follow with delay the behaviour of men (i.e. the youngest women start considering self-employment as a possible first job in their working lives).

As expected, for both genders, the probability of being in the public sector increases with age (there are age barriers at the entrance into the public sector due to the presence of minimum requirements in terms of education level and age) and reaches a peak at 50-55 (the number of public workers increased in the 1970s following the creation of new public administrations and the enlargement of the already existing bodies).

Let us come back to Table 10 and 12 to examine the effect of the regional unemployment rate. For men, this effect on the probability of being in the private sector is strongly negative, meaning that a higher

[27]In other words, the dramatic increase in the female unemployment rate is explained by the fact that women have entered the labour market much faster than the labour market was able to absorb them.

unemployment rate corresponds to fewer opportunities of finding a job in the private sector due to a reduced capacity of this sector to offer jobs. In consequence, the alternantives - with positive elasticities - are those offered by self-employment and public sector; this latter has been purposely enlarged by the government in periods of increasing unemployment and in regions with high unemployment rates. In the case of women, on the contrary, the regional unemployment rate produces much smaller effects. Elasticity for the private sector is negative, but much lower than in the case of men; for the public sector it is almost zero and it is positive for self-employment. The fact that all these effects are, for women, quite small supports the previously presented argument that the unemployment rate should be interpreted differently for men and women. In the case of men this is almost completely due to changes in the demand-side of the labour market, i.e. to a reduction of the total number of male employees, while in the case of women it is due to changes in both the demand-side and the supply-side. In this case it could be compatible with an increasing or constant number of places available in the private sector for female workers.

The effect due to variation in family wealth is negative for the private and public sectors, and for both genders, as expected, and probably indicates the existence of financial barriers in entering self-employment; as wealth increases, the probability of being self-employed also increases.

As far as the effect of the presence of other sources of income in the family is concerned, we have two variables on which to rely: the number of other income recipients and the total amount of other family earnings. The increase in the number of other income recipients increases the probability of being self-employed and decreases that of being public workers, both for men and women (see Table 13 and Table 14 respectively). This result may be due to behaviour which is aimed at reducing the risk (and therefore the self-employed choice is possible only if there are other income recipients in the family), but also to the specific way of organizing the productive activity by the self-employed, i.e. in the form of family enterprises. In Italy (and in our sample), the members of family enterprises represent a large proportion of the self-employed.[28] When looking at the effect of the total annual amount of income earned by other family members we are probably surprised by the negative sign of the elasticity in the case of self-employment, for both men and women (see Table 10 and Table 12 respectively), which means that workers whose family can rely on less additional financial support are more likely self-employed. However, a negative sign is compatible with the explanation of the existence of many self-employed people who are members of family enterprises; the family enterprises - active in sectors like agricolture and trade - declare very low income levels.

The increase in other personal earnings has a positive effect on the probability of being both in the private and in the public sector and a negative effect on the probability of being self-employed. Unfortunately, we do not know the nature if these earnings (income from a second job, pensions, interests from bonds, dividends, etc.). Anyway, it is likely that a worker whose main job is self-employed activity has only this job;[29] moreover, he will probably invest the profits in his activity. This is a possible explanation for the negative elasticity of the other personal earnings on the probability of being self-employed.

It is interesting to examine the effect of changes in the education level. For both the typical man and woman, the probability of being self-employed is the highest at very low and very high levels of education. This highlights the existence of a great heterogeneity inside the group of the self-employed. In fact, the level of education varies considerably across the various categories of the self-employed, from the very low level typical of the members of family enterprises and enterpreneurs to the highest levels which characterize the professionals. For women, high levels of education considerably increase the probability of having a job in the public sector.

The highest probability of being in the public sector when living in

[28] In our sample more than one fourth of all self-employed are members of family enterprises.

[29] An individual who is an employee and self-employed will probably declare himself as an employee as a first job.

the South is clearly confirmed for women and also for men; Southern male workers, however, have also a high probability of being self-employed, while the female average worker has the highest probability of being self-employed when living in the North-East. The highest probability of working in the private sector corresponds, for both genders, to the North-West of the country.

If we associate an increase of risk to situations like "house not owned" and "being head of the family", we will notice - consistently with our expectations - an increase in the probability of being self-employed, the status requiring the highest "risk propensity", both for men and for women.

4.4.3 A possible interpretation for rho

What is left, at this point, is an attempt to interpret rho. In our estimated model, rho is the correlation between the the difference between the utility of being private and the utility of being self-employed and the difference between the utility of being public and the utility of being self-employed,[30] conditional on the explanatory variables, i.e. once the effect of the regressors has been taken into account.

For both genders this correlation is strongly negative. This fact indicates that the more the worker "confuses" the utility of being self-employed and the utility of working in the private sector, the more he distinguishes between the utility of being self-employed and the utility of working in the public sector and vice versa. In other words, when the self-employedactivity and the private job are considered as very close in terms of preferences, the public job is regarded as strongly "far", i.e. strongly different from the self-employment and therefore from the private job. The negative sign of rho implies that the opposite is also true, even if, from the economic point of view, the interpretation of this second case is more arduous. In fact, a certain closeness between private

[30]The correlation in terms of differences between utilities arises because of the normalisation adopted for identification reasons.

job and self-employedactivity is a predictable result. Both sectors are generally characterized by scope for personal initiative, possibility of career, greater motivation and responsibility in comparison with the public job. Similarities between self-employment and the public job, on the contrary, are difficult to find. However, a negative correlation does not mean that both polar cases are equally likely; the first case is in our view the most sensible situation. Moreover, in both cases an evident distance between the public and the private sector worker type is clearly predicted.

This result seems to us very interesting. A priori, in fact, one could expect to find similarities between the private and the public job in that they are both employed job. The distinction between self-employedand employed job emphasises the existence of financial constraints as the crucial reason for entering the one or the other sector. Looking at the estimated rho, instead, a diversity of the public *versus* the private job clearly arises and this indicates that family wealth is only one of the relevant explanatory variables and that other personal characteristics are more important in determining the "worker type".

5 Conclusions

This attempt to analyse the workers' occupational choice offers an answer to several questions, but at the same time widens the scope for further investigations. Among the main findings, the one which seems to us to be the most relevant is the existence of a negative correlation between the utility of working in the private sector and the utility of working in the public sector, conditional on the explanatory variables entering the model. Although this result is in accordance with a general a-priori expectation, it is nevertheless interesting to find that the data strongly support this intuition. The possibility of defining the sectors according to the legal nature of the employer is also confirmed by the significance of many variables in the probit equation. Even if rationing situations have not been taken into account, a certain degree of similarity among individuals working in the same sector arises from the analysis.

Possible extensions suggested by the results obtained so far include, for women, the consideration of a fourth, relevant choice, namely, to stay out of the labour force. It is in fact evident that, especially in certain areas (such as, for example, the South, which is characterized by a high unemployment rate), many women decide not to work instead of accepting a job in a non-preferred sector. Another possible development of this work would consist in enlarging the number of alternatives by disaggregating the three sectors considered in homogeneous occupational groups, such as, for example, white and blue collars, or in working time regimes like full-time and part-time.

Appendix

A.1 List of variables

Variable	Description
age:	age of individual at 31.12.1993
age2:	age squared
assets:	dummy=1 if the individual owns risky assets (shares, fondi comuni, etc.)
blue:	dummy=1 if the individual is a blue-collar worker
burden:	no. of non-earners/no. of total members in the family
child6:	no. of children aged less than 6 in the family
comune1:	dummy=1 if the ind. lives in a *comune* with less than 20.000 inhab.
comune2:	dummy=1 if the ind. lives in a *comune* with 20.000 to 40.000 inhab.
comune3:	dummy=1 if the ind. lices in a *comune* with 40.000 to 500.000 inhab.
educ2:	dummy=1 if the individual has at most the primary education level
educ3:	dummy=1 if the individual has at most the high school education level
educ4:	dummy=1 if individual has a degree or a post-graduated education level
North-West:	dummy=1 if the individual lives in the North-West of Italy
North-East:	dummy=1 if individual lives in the North-East of Italy
Centre:	dummy=1 if individual lives in Central Italy
headfam:	dummy=1 if the individual is the head of the family
house:	dummy=1 if the ind. owns at least 50% of the house in which he lives
manager:	dummy=1 if the individual is a manager or a top manager
married:	dummy=1 if the individual is married or livetoghether with a patner
mobil:	dummy=1 if the ind. has changed job at least 3 times in his work. career
nrecip:	total number of income recipients in the family
otherfi:	total annual amount of all other family income, excluding the earnings of the individual in million Lit.
otherfi2:	otherfi squared
otherpi:	total annual amount of all other personal income of the individual, excluding the earings from the main activity, in million Lit.
otherpi2:	otherpi squared
prevexp:	years of total work experience at the time of starting the present job
prevexp2:	prevexp squared
pwagepr:	predicted hourly wage in the private sector (logarithm of thousand Lit.)
pwagepr2:	pwagepr squared
pwagepu:	predicted hourly wage in the public sector (logarithm of thousand Lit.)
pwagepu2:	pwagepu squared

runrate:	regional male/female unempl. rate at the time of starting the present job
sectagric:	dummy=1 if the ind. works in agricolture
sectbank:	dummy=1 if the ind. works in the banking and insurance sectors
secteduc:	dummy=1 if the ind. works in the education and health sectors
tenure:	number of total years worked in the present job or activity
tenure2:	tenure squared
wealth:	total amount of wealth at 31.12.1993, in billion Lit. (value of immovables, land, shares, etc.)
wealth2:	wealth squared

A.2 Multinomial logit results for prediction of wages

Table A.1:multinomial logit estimates - men[1]

Loglikelihood=-4291.54, 4800 obs., Pseudo $R^2 = 0.1521$

Variable	**Coeff.**	**S.E.**	**z**		**Coeff.**	**S.E.**	**z**
Private				*Public*			
age	-0.1299	0.0271	-0.479		0.1605	0.331	4.846
age2	-0.0002	0.0003	-0.749		-0.0015	0.0004	-4.223
educ2	0.0564	0.1100	0.513		1.3220	0.1380	9.581
educ3	0.2174	0.1184	1.836		1.8071	0.1443	12.516
educ4	-0.4348	0.1788	-2.432		2.3012	0.1807	12.729
headfam	-0.5529	0.1303	-4.244		-0.0335	0.1509	-0.222
North-West	0.3108	0.1406	2.210		-0.6547	0.1544	-4.239
North-East	0.0881	0.1448	0.608		-0.5920	0.1564	-3.785
Centre	0.1739	0.1294	1.344		-0.1173	0.1355	-0.866
otherfi	0.0137	0.0024	5.698		0.0152	0.0029	5.278
otherpi	0.0590	0.0076	7.798		0.0257	0.0067	3.797
otherpi2	-0.0006	0.00007	-5.494		-0.0001	0.0001	-2.436
wealth	-3.6732	0.2169	-16.938		-3.6823	0.2492	-14.777
wealth2	0.3576	0.0301	11.860		0.3033	0.0318	9.542
house	0.3030	0.0962	3.150		0.4299	0.1078	3.988
mobil	0.4724	0.1150	4.106		0.0617	0.1344	0.459
burden	0.9947	0.1824	5.452		1.1325	0.2056	5.508
child6	-0.4580	0.0851	-5.381		-0.2401	0.0896	-2.678
runrate	-4.9629	1.5939	-3.114		-4.0424	1.7222	-2.347
constant	1.8963	0.5936	3.195		-4.6713	0.7474	-6.250

[1]Equation 1 corresponds to the private sector, Equation 2 to the public sector, the outcome status=self-employment is the comparison group.

Table A.2: multinomial logit estimates - women

Loglikelihood=-2078.37, 2667 obs,PseudoR^2 = 0.2587

Variable	Coeff.	S.E.	z		Coeff.	S.E.	z
Private				*Public*			
age	0.0097	0.0430	0.227		0.1949	0.0460	4.240
age2	-0.0009	0.0005	-1.668		-0.0021	0.0005	-3.948
educ2	-0.2431	0.1755	-1.385		0.9460	0.2096	4.514
educ3	0.2016	0.1974	1.021		2.8294	0.2188	12.932
educ4	-0.7989	0.2999	-2.664		3.2181	0.2741	11.741
*comune*1	-0.4961	0.1400	-3.543		-0.4468	0.1496	-2.987
married	-0.9131	0.1601	-5.703		-0.7559	0.1680	-4.500
North-West	0.4291	0.2148	1.998		-0.7201	0.2111	-3.412
North-East	-0.0122	0.2156	-0.057		-0.9427	0.2127	-4.432
Centre	0.2809	0.1913	1.468		-0.6942	0.1887	-3.679
otherfi	0.0377	0.0065	5.785		0.0346	0.0067	5.124
otherfi2	-0.0002	0.00004	-4.207		-0.0001	0.00004	-3.340
wealth	-3.9618	0.3157	-12.550		-3.4683	0.3105	-11.169
wealth2	0.5638	0.0688	8.198		0.4401	0.0656	6.704
house	0.5268	0.1476	3.568		0.5153	0.1553	3.318
assets	0.3752	0.2059	1.822		-0.2549	0.2104	-1.212
nrecip	-0.0660	0.0894	-0.738		-0.3007	0.0989	-3.042
runrate	-4.6600	1.0207	-4.566		-6.0488	1.0070	-6.007
constant	2.7613	0.9358	2.951		-2.9714	1.0307	-2.883

Table A.3: wage regression - men

Private sect.: 2273 obs., ad. $R^2 = 0.46$.

Public sect.: 1317 obs., ad. $R^2 =$

0.34.*Thedependentvariableisthelogarithmoftheobservedhourlywageintheprivateandpubli*

Variable	Coeff.	S.E.		Coeff.	S.E.
Private			*Public*		
lambda	0.2334	0.0359		-0.0354	0.0381
educ2	0.1015	0.0787		0.1138	0.0555
educ3	0.2000	0.0773		0.2464	0.0578
educ4	0.3110	0.0887		0.5717	0.0671
tenure	0.0221	0.0040		0.0212	0.0038
tenure2	-0.0003	0.0001		-0.0003	0.0001
prevexp	0.0104	0.0017		0.0095	0.0033
prevexp2				-0.0004	0.0001
North-West	0.1987	0.0350		0.0214	0.0324
North-East	0.1340	0.0364		0.0531	0.0313
Centre	0.0768	0.0362		0.0413	0.0256
sectbank	0.1834	0.0334			
secteduc				0.0086	0.1091
manager	0.2148	0.0311			
blue	-0.1843	0.0897		0.1216	0.1030
educ2*b.	-0.0709	0.0815		-0.0391	0.0699
educ3*b.	-0.0638	0.0831		-0.0911	0.0913
educ4*b.	-0.5805	0.3389		-0.5958	0.3153
tenure*b.	0.0092	0.0047		-0.1308	0.0076
tenure2*b.	-0.0004	0.0001		0.0003	0.0002
prevexp*b.	-0.0049	0.0019		-0.0087	0.0068
prevexp2*b.				0.0003	0.0002
North-West*b.	0.0609	0.0400		0.0557	0.0659
North-East*b.	0.1113	0.0422		0.0044	0.0597
Centre*b.	0.0926	0.0334		0.0084	0.0534
constant	1.7509	0.0852		2.1258	0.0951

Table A.4: Private wage regression - women
Private sect.: 1078 obs., ad. $R^2 = 0.34$.
Public sect.: 1051 obs., ad. $R^2 = 0.42$.

Variable	Coeff.	S.E.		Coeff.	S.E.
Private			*Public*		
lambda	0.2305	0.0419		0.0588	0.0453
educ2				0.2269	0.0924
educ3				0.4497	0.0975
educ4	0.3167	0.0705		0.8238	0.1057
tenure	0.0267	0.0063		0.0203	0.0040
tenure2	-0.0005	0.0003		-0.0002	0.0001
prevexp	0.0182	0.0066		-0.0083	0.0049
prevexp2	-0.0006	0.0002		0.0003	0.0002
North-West	0.1959	0.0518		-0.0765	0.0307
North-East	0.1782	0.0522		-0.0653	0.0315
Centre	0.1343	0.0525		-0.0144	0.1423
*comune*1	0.0377	0.0603			
*comune*2	-0.0818	0.0580			
*comune*3	-0.0529	0.0495			
sectagric	0.2729	0.1470			
sectbank	0.1457	0.0456			
blue	-0.3675	0.1032		-0.0144	0.1424
manager				-0.0723	0.0447
educ2*b.				-0.1803	0.1111
educ3*b.				-0.1493	0.1232
educ4*b.				-0.1625	0.3307
tenure*b.	-0.0167	0.0080		-0.0038	0.0127
tenure2*b.	0.0002	0.0003		0.0000	0.0004
prevexp*b.	-0.0123	0.0081		-0.0023	0.0109
prevexp2*b.	0.0004	0.0003		-0.0000	0.0004
North-West*b.	0.3114	0.0697		0.0894	0.0849
North-East*b.	0.2627	0.0715		0.2183	0.0962
Centre*b.	0.2064	0.0713		0.2074	0.0896
*comune*1*b.	-0.0236	0.0926			
*comune2**b.	0.2069	0.0926			
*comune*3*b.	0.1355	0.0852			
sectagric*b.	-0.4274	0.0456			
constant	1.7303	0.0728		1.9129	0.1272

A.3 Multinomial logit and constrained covariance probit results

Table A.5: logit estimates[2] - men

Loglikelihood= -3863.32, 4790 obs.
Stars denote unsignificance at 5% level.

Variable	Coeff.	S.E.		Coeff.	S.E.
Private			*Public*		
age	0.3447	0.0325		0.1652	0.0342
age2	-3.6157	0.3724		-1.7940	0.3885
educ2	0.7379	0.1300		0.9570	0.1489
educ3	1.7760	0.1612		1.0501	0.1830
educ4	0.8305	0.2516		0.1585*	0.3346
North-West	0.9341	0.1504		-0.5463	0.1532
North-East	0.6307	0.1530		-0.5443	0.1540
Centre	0.4730	0.1377		-0.1073*	0.1345
otherfi	0.0175	0.0031		0.0209	0.0034
wealth	-2.8402	0.2391		-3.6989	0.2535
wealth2	0.2821	0.0378		0.2972	0.0293
house	0.3509	0.1025		0.5174	0.1085
nrecip	-0.1060*	0.0659		-0.3009	0.0737
otherpi	0.0378	0.0056		0.0208	0.0061
otherpi2	-0.5854	0.0588		-0.1418	0.0628
runrate	-13.5971	1.8668		-1.0045*	1.8924
pwagepr	-54.7612	2.3371			
pwagepr2	10.1066	0.4611			
pwagepu				-17.0210	3.6780
pwagepu2				3.7984	0.7381
constant	65.2070	2.7849		15.3602	4.6158

[2] In this table and in the following Table A.6 the variables age2 and otherpi2 have been rescaled by division by 1000 for computational reasons.

Table A.6: constrained covariance probit estimates - men

Loglikelihood=3807.073, 4790 obs.

Stars denote unsignificance at 5% level.

Variable	St. Val.	Coeff.	S.E.		St. val.	Coeff.	S.E.
Private				*Public*			
age	0.1920	0.2133	0.0182		0.0920	0.0902	0.0187
age2/1000	-2.0139	-2.2139	0.2052		-0.9992	-0.9472	0.2143
educ2	0.4110	0.3794	0.0707		0.5330	0.5392	0.0801
educ3	0.9892	1.0314	0.0931		0.5849	0.5083	0.0992
educ4	0.4626	0.4883	0.1470		0.0883	0.1175*	0.2003
North-West	0.5202	0.6988	0.0804		-0.3043	-0.4050	0.0827
North-East	0.3513	0.4969	0.0806		-0.3032	-0.3664	0.0833
Centre	0.2634	0.3195	0.0721		-0.0597	-0.1115*	0.0726
otherfi	0.0098	0.0081	0.0018		0.0116	0.0095	0.0019
wealth	-1.5820	-1.2210	0.1473		-2.0603	-1.7191	0.1799
wealth2	0.1571	0.1264	0.0223		0.1655	0.1391	0.0169
house	0.1954	0.1431	0.0569		0.2882	0.2427	0.0640
nrecip	-0.0590	-0.0423*	0.0368		-0.1676	-0.1622	0.0406
otherpi	0.02108	0.0213	0.0029		0.0116	0.0092	0.0033
otherpi2/1000	-0.3261	-0.3571	0.0224		-0.0790	-0.0531*	0.0325
runrate	-7.5734	-7.5901	1.0140		-0.5595	0.8958*	1.0660
pwagepr	-30.5014	-35.0997	1.5218				
pwagepr2	5.6292	6.4055	0.2980				
pwagepu					-9.4805	-6.2247	2.2149
pwagepu2					2.1157	1.5360	0.4470
constant	36.3195	42.0699	1.7776		8.5554	3.7805*	2.7431

Table A.7: logit estimates[3] - women

Loglikelihood= -1963.48, 2653 obs.

Stars denote unsignificance at 5% level.

Variable	Coeff.	S.E.		Coeff.	S.E.
Private			*Public*		
age	0.1583	0.0487		0.1976	0.0498
age2/1000	-2.2787	0.5942		-2.3550	0.5953
educ2	0.1516*	0.1940		0.7909	0.2249
educ3	1.0280	0.2276		2.5376	0.2964
educ4	0.4947*	0.4023		1.6113	0.4920
married	-0.7849	0.1799		-0.7442	0.1832
North-West	1.1487	0.2422		-0.5650	0.2355
North-East	0.6558	0.2427		-0.7760	0.2322
Centre	0.6716	0.2155		-0.5463	0.2075
otherfi	0.0324	0.0071		0.0316	0.0070
otherfi2/1000	-0.1291	0.0430		-0.1163	0.0419
wealth	-3.0058	0.3531		-3.5698	0.3325
wealth2	0.3955	0.0743		0.4293	0.0674
house	0.2422*	0.1577		0.4412	0.1618
nrecip	-0.1919	0.0945		-0.2822	0.1007
otherpi	0.1034	0.0214		0.0497	0.0169
otherpi2/1000	-1.1178	0.3826		-0.2721*	0.1750
pwagepr	-18.4103	2.7279			
pwagepr2	3.3284	0.6032			
pwagepu				-31.2194	4.8038
pwagepu2				6.5027	0.9921
headfam	-0.8562	0.2498		-0.3404	0.2483
runrate	-6.0766	1.1326		-5.5242	1.1189
constant	23.0202	3.1000		34.5199	5.9513

[3]In this table and in the following Table A.8 the variables age2, otherfi2 and otherpi2 have been rescaled by division by 1000 for computational reasons.

Table A.8: constrained covariance probit estimates - women

Loglikelihood=-1931.02, 2653 obs.

Stars denote unsignificance at 5% level.

Variable	St. val.	Coeff.	S.E.		St. val	Coeff.	S.E.
Private				*Public*			
age	0.0881	0.0868	0.0255		0.1101	0.1302	0.0257
age2/1000	-1.2692	-1.2255	0.3147		-1.3117	-1.4682	0.3184
educ2	0.0844	0.03897*	0.0975		0.4405	0.4576	0.1212
educ3	0.5726	0.3691	0.1178		1.4134	1.3714	0.1710
educ4	0.2755	0.1432*	0.2212		0.8975	0.7911	0.2958
married	-0.4372	-0.3647	0.0899		-0.4145	-0.3157	0.0918
North-West	0.6398	0.7886	0.1257		-0.3147	-0.4371	0.1242
North-East	0.3653	0.5209	0.1266		-0.4322	-0.5002	0.1234
Centre	0.3740	0.4923	0.1134		-0.3043	-0.3609	0.1106
otherfi	0.0180	0.0137	0.0037		0.0176	0.0132	0.0037
otherfi2/1000	-0.0719	-0.0570	0.0216		-0.0647	-0.0446*	0.0230
wealth	-1.6742	-1.2572	0.2018		-1.9883	-1.7298	0.1864
wealth2	0.2203	0.1672	0.0330		0.2391	0.1987	0.0375
house	0.1349	0.0909*	0.0824		0.2457	0.2536	0.0850
nrecip	-0.1069	-0.0810*	0.0520		-0.1572	-0.1483	0.0552
otherpi	0.0576	0.0591	0.0121		0.0277	0.0155*	0.0096
otherpi2/1000	-0.6226	-0.7868	0.2362		-0.1516	-0.0714*	0.1013
pwagepr	-10.2543	-12.4721	1.6871				
pwagepr2	1.8539	2.1999	0.3750				
pwagepu					-17.3888	-20.3259	2.8241
pwagepu2					3.6219	4.3023	0.5841
headfam	-0.4769	-0.4953	0.1284		-0.1896	-0.0716*	0.1332
runrate	-3.3846	-3.1041	0.6125		-3.0769	-2.5081	0.6062
constant	12.8220	15.7031	0.9181		19.2271	21.4746	3.5025

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